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Genetic Algorithms for Automised Feature Selection in a Texture Classification System

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Abstract

This paper describes the usage of genetic algorithms as feature selectors in a texture classification system. This is part of a system developed within a research project concerning the classification of genuine texture. An attempt is made to underline why an automised feature selector is a useful part of the texture classification system. Furthermore the way of including the genetic algorithms into the system and the necessary feedback structure is explained.

1 Introduction

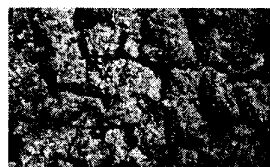
The real world does not supply the laboratory conditions that are necessary for the majority of the existing image processing systems. Therefore all those ill structured or coarse grained objects and especially objects without clear boundaries are a major problem in the field of object recognition. In some areas it is even problematical to speak of objects in the classical sense. One only has to think of a cornfield, a lawn, ripples on water, clouds in the sky or leaves on a tree to comprehend the problems.

The aim of the research work of which this paper describes a part is to find a solution to the problem of classifying genuine texture, as texture represents the unstructuredness very well. Some alternative and completely new methods are being developed and tested. Furthermore existing approaches for sub-problems are included in the system. This system shall not be adapted for a special problem but shall be universal. Therefore it can be used for multiple tasks in many fields, e.g. medicine, remote sensing, machine vision, etc.

This paper describes the part that brings self optimisation into the system. Genetic algorithms have been chosen to effectively minimise the set of features statistically extracted in prior modules of the system. Such minimisation is necessary to reduce the dimension of

the following classification modules.

2 What is Texture?



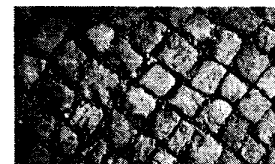
(a) Bark of an old birch tree.



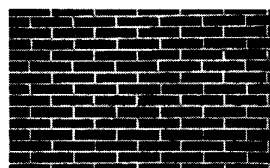
(b) Blades of grass covered with frozen dew.



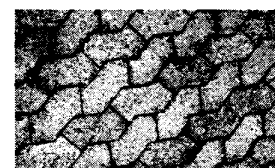
(c) Field of clouds against blue sky.



(d) Cobblestones with unstructured edges.



(e) Brick wall with white mortar.



(f) Interlocking paving-stones.

Figure 1: Pictures of natural, half-natural and man-made texture.

There is no unique definition of the word *texture*, but rather a context dependent description. It descends from the Latin word *texere* ("to weave") and the WEB-

STER [16] definition closest to the use in image analysis is *similar qualities dependent on the nature and arrangement of the constituent particles of a substance*.

In general it can be said that a texture describes the surface composition of an object. Texture can be divided into regular and statistical texture. Regular texture is composed of repeated texture primitives which are large against the pixel resolution and could be described in further detail (cf. fig. 1(e), 1(f)), whereas the elements of a statistical texture near unity and have a random distribution (cf. fig. 1(a), 1(b), 1(c)). Very often texture is of a hierarchical kind where the macro texture is regular and the micro texture of the primitives statistically describable.

For testing the system only genuine texture is being used. Genuine texture comprises all those textures that are not artificially constructed, i.e. made on and for a computer. The group can be subdivided into natural, half-natural and man-made texture.

3 Statistical Feature Extraction

One way of classifying texture is by using statistical methods for feature extraction. Such methods are used in this texture classification system.

Before the statistical methods are applied some preprocessing methods are used. These aim at the reduction of redundant information contained in the texture images so that the relevant information can be extracted more easily.

Currently used methods are a preliminary median filtering after a subimage has been extracted followed by a number of image analysis methods. Among these are different kinds of edge detection, gradient extraction, SOBEL filtering, surface and spectral analysis [12]. Next to those standard methods the images are processed through wavelets filters [5] and LAWS-measures [8]. The results of these computational steps are not used in the classical sense—it is for example not of interest where edges can be found—but are statistically evaluated.

Statistical calculations are performed on the preprocessed subimages, for each of which the mean value, variance, standard deviation, root mean square, maximum and minimum value, the integral, skewness, kurtosis, entropy and contrast are among those computed.

Additionally high order statistics are used as in texture analysis the neighbourhood relations are of importance. Very good results have been obtained concerning the orientation of similar grey-level pixels within a texture. The spatial grey-level dependence (SGLD) matrices used yield potential features, among which are the entropy, correlation, inertia and homogeneity [3].

All this results in a vast amount of data, but only a fraction of the extracted features provide information that is unique to a specific texture. Therefore the number of features has to be reduced to avoid wasting computational resources.

4 Feature Selection using Genetic Algorithms

As the number of features generated in the previous modules of the system is very large it is necessary to select relevant features for the classification which takes place in the following modules. Doing this manually is not an option as the dimension of the feature plane is by far too large to be visualisable and the possible connections between features too complex. Therefore an automatised feature selector has to be included into the system.

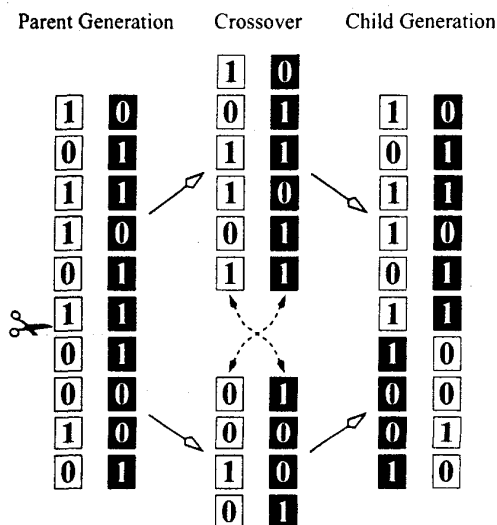


Figure 2: Crossover

Genetic algorithms have the capability of finding very good local or even global optimal solutions in complex data-planes [11]. Therefore every feature is associated to one *gene*—a boolean element—and all genes compose the equivalent of a *DNA*. If the gene is set to zero the associated feature is not used in the following modules of the system and it is used if the gene is set to one. One half of the starting population is created randomly, the other half consists of the negated first half. In the next step all or some members of the population are used to create a new generation by exchanging parts of the DNA-string. This is called *crossover*.

Depending on the way of selection and production of DNAs the population can grow rapidly. Additionally some DNAs can be mutated to avoid getting stuck in a local optimum.

Figure 2 shows graphically how the crossover works. The spot where the DNA-string is cut is chosen by random.

Next to the algorithm itself the fitness evaluation is most important. Fitness evaluation is the performance test of the system using every DNA of the population and thus a number of sets of selected features. After those tests only the better DNAs stay in the population and the production of a new population starts again.

This process continues as long as the fitness differences between parent and child population are significantly different for a specified number of generations.

In this case the fitness describes the ability to distinguish between different texture images. Figure 3 gives an idea how the features that describe a certain texture build a cluster in the feature plane. The aim is to find such a selection of features for which the cluster do not intersect with one another. The better the clusters are kept apart, the easier the classification is.

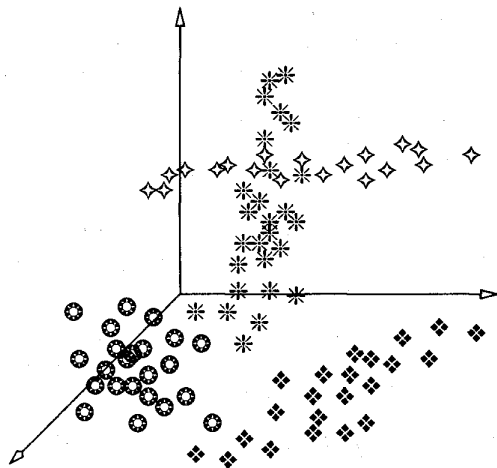


Figure 3: Cluster in a 3D-feature-plane

5 Classification

As the aim is to find the relevant features to classify texture classes a system had to be developed that handles the multi-dimensional feature vectors. Additionally it had to provide the possibility to judge the relevancy of the features.

5.1 Fuzzy Clustering

One possibility of classifying the feature vectors is using a clustering system [6], [9], [15]. For each (relevant) feature a new dimension is created. This results in an n -dimensional plane. All vectors that belong to a specific texture class make up a set, or cluster, which is diverse to all other texture clusters in this plane. With increasing numbers of texture classes the chance of clusters overlapping in one or more dimension increases. Therefore new methods had to be adopted to overcome this problem.

Fuzzy logic methods have a potential for handling uncertain knowledge [13], [17], [19]. Thus it is possible to classify textures of which the feature vectors do not point to the center of a certain texture cluster but into an overlapping area of two or more clusters [1], [2], [4], [14]. Such a texture has a membership value of a certain height for every cluster of the plane. Usually this value equals zero for almost all clusters and obtains a high value for the texture cluster in question. Textures that have membership values of about equal height have to be treated in a postprocessing system.

5.2 Neural Networks

An alternative to fuzzy clustering is to use neural networks. Widely known backpropagation (BP) networks have been successfully tested for this task [7], [10]. One problem with BP networks is that they are not retrainable, i.e. new texture classes can not be added without destroying the trained classes. This makes it more difficult and time consuming to expand the number of texture classes.

A neural network type which overcomes these problems is the adaptive resonance theory (ART) family [18]. Networks of this type can be retrained at any time. These networks are currently included into the system.

A general problem with neural networks is the rather long training time and the great need for computational resources, especially when input (number of features) and output (number of classes) vectors are large in size. In such cases the use of special neural network hardware is almost unavoidable, especially if the network has to be trained again and again to find the optimal feature vector as in the case of this texture classification system.

6 The System

The Texture Classification System is composed of modules and layers. Figure 4 shows a simplified lay-

out of the complete system. The centerpiece is the Core-System which consists of three modules: the pre-processing methods, the statistical methods and the soft-computing methods. The Core-System classifies single-texture images and is itself the center module of the Enhanced-System with the image preparation module before and the postprocessing module after it. The Enhanced-System is capable of identifying single-texture regions within a multi-texture image and thus finding borders between texture regions. The Automated Optimization System is made up of the genetic algorithm module and the fitness evaluation module. This subsystem can be used for optimization tasks throughout the complete system. The paper only describes the use for the feature vector size optimization.

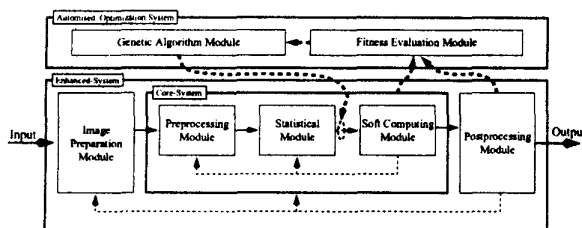


Figure 4: Texture Classification System

7 Conclusions

This paper has introduced the use of genetic algorithms as feature selectors in a texture classification system. The necessity and advantages of this approach have been delineated and discussed. Problems associated with the actual textures themselves and other modules of the system have also been addressed.

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